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Proceedings of the 7th International Seminar on ORC Power Systems

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Guidelines and optimization criteria of a machine learning-based methodology for mixture design in ORC systems

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ABSTRACT

Working fluid selection in organic Rankine cycles (ORC) is a critical issue in the system design for specific applications. In most cases, pure fluids are employed as working medium, and the choice among commercial products is fundamentally based on the heat source temperature level, on fluid cost and safety requirements. Mixtures of organic fluids present some interesting features. First of all, zeotropic blends can help reducing the irreversibility associated to the isothermal heat transfer of pure working fluids in the evaporator and in the condenser, with potential improvement of the overall conversion efficiency from heat sources with finite capacity. Moreover, the possibility of using fluids with relatively high global warming potential, blended with low-GWP fluids, allows reducing the equivalent carbon emissions (according to the European F-gas regulation), helping the full transition to cleaner compounds. However, there is a lack of organic mixtures specifically optimized for ORC systems, particularly because different applications require fluids with different properties, and the available solution may not be the optimal for the specific case. Due to the large number of molecules available to be combined, the use of numerical algorithms is mandatory to accomplish the mixture formulation task (type, number and amount of each component). In this work, an optimization tool based on a Bayesian statistical inference methodology is implemented and tested, to define the composition of mixtures of different groups of organic fluids (HFC, HFO, HC). The algorithm adopts a mixed exploration-exploitation searching strategy on a solution domain made by the different pure molecules commonly employed. The tool is programmed to fulfil the maximization of an objective function, built from a set of key physical properties and performance indexes of the mixture. The choice of the properties accounted in the optimization (with relative weight) is discussed, and the algorithm is applied to a case study to demonstrate its capability to define a low-GWP blend replacing HFC 134a, maintaining and possibly enhancing the performance.

1 INTRODUCTION

The use of mixtures of working fluids in organic Rankine cycle is gaining attention due to some favourable characteristics. Mixtures can be used for achieving target values of thermodynamic properties, or for reducing undesired properties of pure molecules, such as high Global Warming Potential (GWP) or flammability. For zeotropic mixtures, the continuous variation of temperature during the phase change may enhance the temperature match between working fluid and heat source, reducing exergy losses and increasing the power output (Angelino and Colonna di Paliano, 1998; Bamorovat and Kim, 2017). Moreover, the need for replacement of currently used high-GWP fluids may occur by mixing such fluids with low-GWP molecules, especially during the transition to clean fluids. Fluids with good thermo-physical properties but high value of GWP can be blended with low-GWP fluids to reduce the resulting environmental impact and maintain good thermodynamic properties. Many studies have been published on the optimization of the working fluid in ORC applications, some of them also including binary mixtures. In the most common approach for working fluid choice, a group of fluids is identified based on predefined criteria, and then the optimal substance is obtained by means of a parametric optimization procedure (Freeman *et al.*, 2017). More complex analyses on pure working fluids have been conducted, for example, by Papadopoulos *et al.* (2010); Lampe *et al.* (2014); Cignitti *et al.* (2017); Schilling *et al.* (2021), where a computer-aided fluid selection is integrated in the design of the ORC plant. Integrated design has been less applied to the case of mixture. Some examples are the works by Schilling *et al.* (2021) and by White *et al.* (2018), which extended the computer-aided approach to blends optimization to carry out the thermodynamic and thermo-economic analyses, considering simple non-recuperated subcritical ORC systems.

Due to the large number of independent variables affecting the working fluid performance, together with the highly non-linear behaviour of some of those, classical optimization techniques may face failure. In the current state of the art, different approaches have been adopted to design the proper mixture to employ as working fluid in refrigeration and waste heat recovery applications. Systematic analyses based on iterative routines, constraints from experience and simulation results have shown the potential to fulfil very specific tasks properly in short time (Tang *et al.*, 2022; Sleiti and Al-Ammari, 2022). Some Authors, instead, proposed the use of heuristic techniques aiming at a generally valid method able to perform mixture design without stringent boundaries, e.g., Papadopulos *et al.* (2010) with combined Computer Aided Molecular Design (CAMD) and Simulated Annealing, and Li and Gluesenkamp (2021), with the Particle Swarming Optimization (PSO) technique. Heuristic methods have been widely reviewed and adopted in the current state of the art to attack different engineering optimization tasks (Nazari-Heris *et al.*, 2018), due to their problem simplification power, low computation effort, fast search while ensuring a ‘enough good’ solution. However, those methods lack the ability of finding the global optimum solution and do not provide clear measures of the result quality among all the possible options. It must be considered that the ORC mixture composition design features a wide solution domain (large as the number of possible pure fluids to employ), and high complexity of the optimization function, related to the highly multi-objective nature of the problem (Babatunde and Sunday, 2018). Therefore, ensuring the best composition under given constraints and returning the confidence are key features, thus, alternatives to heuristics should be investigated as well. In this framework, probabilistic techniques are attractive to accomplish the task. However, in the current literature, the use of such methods for ORC working fluid design is scarcely investigated. In particular, Bayesian optimization has the ability to map the solution domain in an efficient manner, thanks to the combined use of a probabilistic surrogate model and a proper acquisition function, which infers according to the Bayes theorem (Stigler, 1982). 274

This work deals with the development of an optimization tool, based on Bayesian inference and aimed at guiding the identification of low-GWP optimized mixtures for ORC applications. The searching algorithm is a modified version of the original work by some of the Authors (Mariani *et al.*, 2021). A set of representative pure fluids as potential mixture components, and a set of constraints have been selected in line with practical observations and the results of an extensive literature review. To demonstrate the methodology capabilities, the code has been run with the aim of replacing R134a with a new azeotropic mixture which mimics its characteristics, while reducing the GWP below 750. This work aims at providing a flexible and user-friendly approach to define optimal ORC mixtures, but it can be applied to any mixture selection procedure for preliminary screening.

2 METHODOLOGY

2.1 Mixture optimization algorithm

The implemented algorithm searches, among the possible mixture compositions, the global maximum of a user-designed objective function according to the general approach described in Mariani *et al.* (2021). In particular, in this study the solution domain is given by the mass fraction of each pure fluid. The searching procedure starts with a Gaussian Process (GP) used as probabilistic surrogate model to determine the belief on the objective function shape over the domain. In the second step, the Upper Confidence Bound (UCB) exploration-exploitation mixed strategy is applied by means of the acquisition function A (Eq. (1)), in which X in the evaluation point, M is the predictive mean, K is the covariance matrix, θ is the exploitation-exploration split hyperparameter, tuned at 0.5. The algorithm has been set in order to perform 50 random initial evaluations, and then 200 evaluations according to the abovementioned strategy.

$$A(X) = M(X) + \theta \cdot K(X) \tag{1}$$

The optimization tool was developed in *Python* 3.0 by means of the *bayes_opt* (https://github.com/bayesian-optimization/BayesianOptimization) open library. The tool is required to define the composition of a mixture, having GWP below 750, able to replace R134a as a working fluid in an ORC cycle for given values of vaporization temperature (75 °C) and condensation temperature (30 °C). Such values have been selected based on the design conditions of the test bench at University of Bologna, which is a micro-ORC for low temperature heat recovery, suitable for renewable thermal sources such as geothermal and solar thermal energy, or for low grade waste heat recovery (Bianchi *et al.*, 2022). The solution domain has been defined by ten different pure fluids comprising: the hydro-fluoro-carbons (HFCs) R134a, R32, R245fa, R227ea, R152a; the hydro-carbons (HCs) propane, i-butane; the hydro-fluoro-olefins (HFOs) R1234yf, R1234ze; the hydro-cloro-fluoro-carbon (HCFC) R142b. The number of fluids selected for the blend optimization is a trade-off between results accuracy and acceptable simulation time. The ten base fluids have been selected among commercial solutions by means of a preliminary screening, mainly based on the value of the critical temperature, keeping in mind that the target is to obtain a surrogate of R134a ($T_C \cong 101$ °C). Another criterion was to include pure fluids from different chemical families. Critical temperatures of the selected fluids are in the interval between 78.4 °C (R32) and 154 °C (R245fa and R1234ze). Due to limitations related to the numerical method, the maximum domain size for each simulation is of 20 fluids. To further increase the total searching domain, multiple runs can be conducted in parallel and/or in sequence.

Once the solution domain has been defined, at each optimization step the performance of the formulated mixtures is evaluated by means of a group of user-defined indicators, which are compared to those of the reference fluid, the R134a. The key indicators, here called 'optimization targets', are: molecular weight (MW) and critical temperature (T_C), both depending only on the fluid (trivial properties); dynamic viscosity (μ), latent heat of vaporization (HoV), liquid and vapor density (ρ_L, ρ_V), liquid and vapor heat capacity (c_L, c_V), and the temperature glide (ΔTG), all evaluated at a fixed pressure; the Jacob number (*Ja*) (Kuo *et al.*, 2011). The latter, defined in Eq. (2), represents a rough thermodynamic estimation of the ORC potential performance provided by the fluid working with T_{vap} and T_{cond} as vaporization and condensation temperatures. Kuo *et al.* (2011) demonstrated that *Ja* is related to the thermal efficiency with inverse proportion. In Eq. (2), the specific heat $\bar{c_p}$ is computed as the average between the specific heat of the saturated vapor at T_{vap} and T_{cond}, while HoV is referred to the heat of vaporization at T_{vap}. The temperature glide is defined as the difference between the saturation temperatures of vapor (T_V) and liquid (T_L) at constant pressure (Eq. (3)) and determines whether the mixture is zeotropic or azeotropic.

$$Ja = \frac{\bar{c_p} \cdot (T_{vap} - T_{cond})}{HoV} \tag{2}$$

$$\Delta TG = (T_V - T_L)_{p=const} \tag{3}$$

This set of properties and parameters has been selected due to their strong bonds with thermodynamic performance and operating issues. For instance, the value of the viscosity affects the volumetric efficiency of the positive displacement machines, as lower viscosity leads in general to higher leakages (Bianchi *et al.*, 2020). In the case of retrofit of an existing ORC system, the replacement of a pure fluid with a mixture characterized by a substantially different value of μ should be accompanied by measures to reduce the leakages in pump and expander. Such measures can be the substitution of the lubricant oil or the modification of the working temperature (to adjust the viscosity), or even the change of one or both the displacement machines with more sealed ones (in case the viscosity difference is high). The density has a direct effect on the fluid mass flow rate and power output, as both decrease with lower values of ρ if the volume flow rate remains the same. The heat of vaporization represents the largest contribution to the heat transferred in the evaporator, hence its variation may causes the change of the mass flow rate if the thermal power input is assumed constant. This is more true in case of recuperated ORC systems, in which an important part of the economization is provided in the recuperator. Finally, the specific heat influence in general both the transferred thermal power and the specific work.

These optimization targets have been combined to design the objective function reported in Eq. (4), in the manner that the optimum mixture lies on a weighted Pareto frontier with the minimum Euclidean distance from the reference fluid. In Eq. (4), φ is the generic optimization target, W is the weight assigned to each optimization target, which can be adjusted in order to change its relevance against the others. The higher is the weight value, the larger is the impact of the optimization target on the final value of the objective function. Thus, higher weight values can be assigned to the properties that are discovered to be difficult to match by the optimizer. Increasing the weight of some optimization targets, may result in worsening of the match of the other optimization parameters with lower weight values. To obtain adequate values of the weights, preliminary runs were performed by setting each weight equal to 1.0. Results revealed that density and heat of vaporization were affected by the larger errors against those of R134a. The successive step consisted in a series of optimization runs, launched increasing progressively the weights of density and heat of vaporization by 0.1. After the preliminary analysis, weights have been tuned to the following values: i) 2.0 for the liquid density; ii) 1.5 for the Jacob non-dimensional number; iii) 1.2 for the heat of vaporization; iv) 1.0 for the remaining optimization targets. Such values have shown the best balance on the absolute relative errors of the optimization targets.

$$F = 100 - \frac{1}{\sqrt{\sum_i W_i}} \cdot \sqrt{\sum_i W_i \cdot \left(\frac{\varphi_{i,R134a} - \varphi_i}{\varphi_i}\right)^2} \tag{4}$$

Eventually, two different arbitrary screening criteria, here called ‘light constraints’, must be fulfilled, namely the solution is discarded if the associated GWP is higher than 750 or if the associated temperature glide is higher than 2.0 K, i.e. if the mixture is zeotropic. As for the optimization targets and the related weights, the screening values can be changed according to the specific objective. For the sake of clarity, the workflow of the described algorithm is reported in Figure 1.

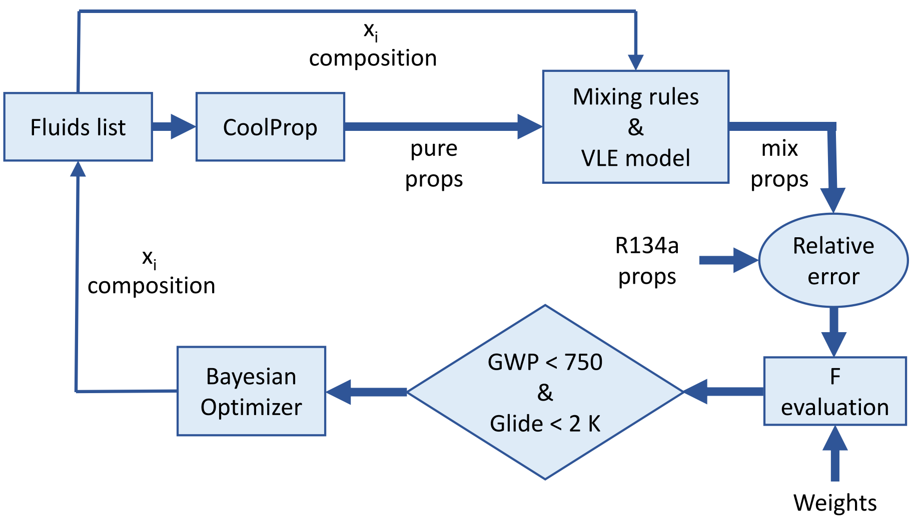

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Figure 1: Workflow of the present mixture formulation and optimization algorithm.

2.2 Mixing rules definition

In order to assess the iterative solutions proposed by the algorithm, methods to estimate both the optimization targets and the light constraints are needed. It must be underlined that the optimization tool is required to perform several iterations, thus, the mixing rules called during the evaluation step should be as simple as possible in order to limit the computation effort. In this work, molecular weight, critical temperature, latent heat of vaporization, density values, heat capacity values, GWP, have been approached as additive quantities, meaning that they are calculated as a weighted average. In particular: i) the mixture critical temperature is calculated as moles weighted average; ii) the mixture latent heat of vaporization, heat capacity, and GWP values are calculated as mass weighted averages; iii) the mixture molecular weight, and density values are calculated as mass weighted inverse averages. Concerning the dynamic viscosity, the moles weighted logarithmic average according to the classical

Grunberg-Nissan correlation (Grunberg and Nissan, 1949) was applied. A simplified version of the original formula was implemented by neglecting the components' cross-term in order to limit to the minimum the use of fitting parameters with arbitrary values.

Once the mixing rules have been defined, the fractions of the single components are provided by the optimizer according to the mixture option under evaluation, whilst the property of those pure components are calculated by calling the *CoolProp* open library (Bell *et al.*, 2014). For the computation of the so-called non-trivial properties, *CoolProp* must be provided with the reference thermodynamics conditions as input. In this work, heat of vaporization, viscosity, and density values are considered at the respective saturated states (liquid or vapor) for the temperature value T that corresponds to the non-dimensional temperature $T^* = T/T_C = 0.7$ (with T and T_C expressed in °C). The value of $T^* = 0.7$ was chosen arbitrarily, as representative of average normalized temperature at which the vaporization process takes place in ORC systems. Instead, the heat capacity values were calculated at saturated states (liquid or vapor) and ambient pressure. It must be pointed out that the expression of the Jacob non-dimensional number (Eq. (2)) involves c_V, HoV, T_{vap}, T_{cond}, thus, it does not require a specific mixing rule, since it has been calculated directly by using the c_V and the HoV of the mixture. Regarding the temperature glide of the new mixture options, since the Vapor-Liquid Equilibrium (VLE) properties are not additive, a dedicated sub model has been implemented to predict the dew point temperature and the bubble point temperature. These two temperature values are calculated according to the pure thermodynamics model presented in Mariani *et al.* (2021). Since the phase equilibrium sub-model is not the focus of the present paper, only the main features will be mentioned, avoiding the extended description of the equations, which can be found in Mariani *et al.* (2021). The bubble point temperature and the dew point temperature problems are numerically solved by means of a system of equations comprising the VLE for each component as a non-ideal fluid, the Soave-Kwong-Redlich cubic equation of state, and the phase mass equilibrium.

2.3 Mixing rules validation

In order to address the optimization tool towards the global best solution, it is important to ensure a high degree of accuracy in estimating the properties used as optimization targets. For the validation procedure, 53 commercial refrigerant mixtures (with known properties) have been taken from the online database W-Refrigerant (https://w-refrigerant.com). Those mixtures are made by different combinations of CFCs (Chloro-Fluoro-Carbons), PFCs (Per-Fluoro-Chemicals), HCFCs, HFCs, HCs, HFOs. For each mixture, the properties resulting from the mixing rules have been compared with those calculated with the commercial software REFPROP 10.0 (Lemmon et al., 2018), which has been assumed as validation benchmark. For the sake of brevity, the validation results are summarized in Table (1), by means of the Root Mean Squared Error (RSME) and the coefficient of determination (R^2). 277

Table 1 shows that the implemented mixing rules have excellent performances in predicting heat capacity of the considered fluid mixtures, with low RSME values and nearly perfect correlation coefficients ($R^2 \approx 1$). The agreement with REFPROPR values for the optimization targets T_C, ρ, HoV is nice as well, whilst the accuracy in predicting μ and ΔTG is slightly lower but still falling in an acceptable confidence.

Table 1: Root Mean Squared Error (RSME) and coefficient of determination (R^2) for each optimization target. Metrics are calculated considering the values from REFPROP 10.0 as a reference.

Optimization target	RSME	R^2
T_C (K)	5.3	0.9141
μ (mPa·s) @T^* = 0.7, Q = 0	5.6 x 10^{-4}	0.8982
ρ (kg/m^3) @T^* = 0.7, Q = 0	5.3	0.9500
HoV (kJ/kg) @T^* = 0.7, Q = 0	10.1	0.9516
c_V (kJ/kg/K) @p = 1 bar, Q = 1	5.2 x 10^{-3}	0.9995
c_L (kJ/kg/K) @p = 1 bar, Q = 0	1.1 x 10^{-2}	0.9980
ΔTG (K) @ p = 1 bar	1.4	0.8814

An in-depth analysis of the data has revealed that the prediction performance loss depends on few mixtures: i) binary mixtures with PFCs (e.g., R508a, R508b, R509a); ii) ternary mixtures of PFCs with HCs (e.g., R403a, R403b, R413a); iii) mixtures containing intermediate quantity of CFC (<40%) (e.g., R500). It must be underlined that due to the high GWP associated to PFCs and the non-zero ODP (Ozone Depletion Potential) of CFCs, those groups will be not included in the optimization routine. Therefore, one can say that this group-dependent prediction derating does not affect the overall reliability of the mixing rules.

3 RESULTS

The focus of this work is the application of the probabilistic Bayesian optimization methodology, with the specific purpose of designing a blend of organic fluids able to mimic the thermodynamic performance of R134a in ORC plants. At the end of the run of 250 iterations, the optimization tool has formulated 50 random, and 200 guided solutions. Among all the resulting mixtures, only 193 fulfil the light constraints of GWP and ΔTG. High-GWP blends are those characterized by a large fraction of R134a, while a glide higher than 2 K is obtained by mixing fluids with large difference of critical temperatures, resulting in zeotropic behaviour. Among the 193 available solutions, the objective function score rises from a minimum of 55 to a maximum of 70.4. In order to focus the analysis to the most relevant solutions, a subset including only the highest fifteen percentile (i.e. mixtures with score from 59.5 up to the maximum) has been selected and is shown in Figure 2.

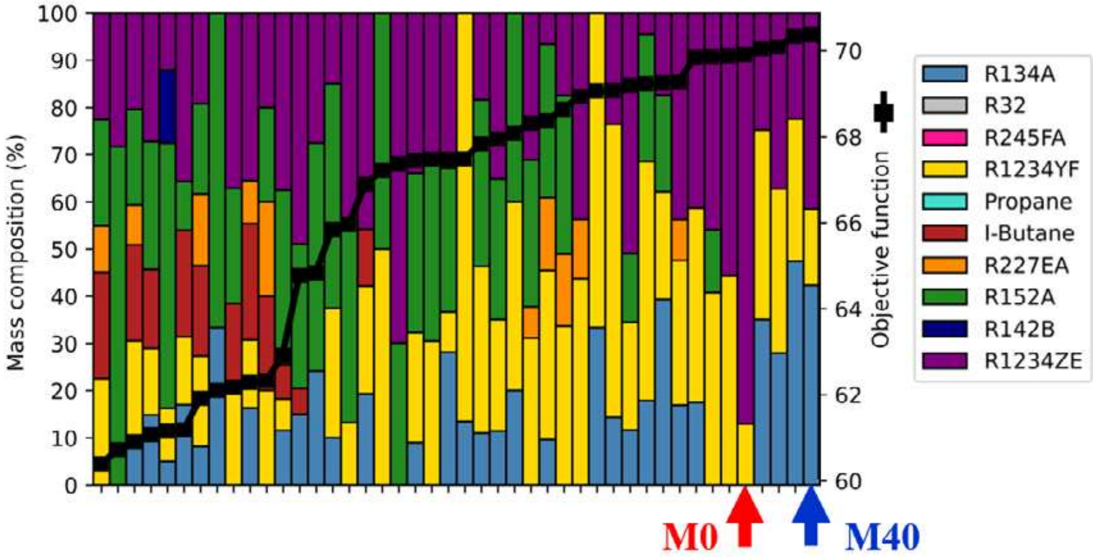

Figure 2: Composition of the mixture solutions proposed as surrogate for R134a (left-hand axis), and the corresponding objective function score (black line, right-hand axis).

Each bar of the graph is a mixture solution, composed of the pure fluids according to the colours in the legend. The mixtures have been ordered according to the value of the objective function, which is shown with the black curve with squared markers referred to the right-hand axis. Figure 2 shows three of the initial components in the database (namely R245fa, R32, and propane) are not employed in any of the best mixtures, whilst the fluid R142b is in one single mixture with score around 61. The absence of the refrigerants R245fa, R32 and R142b is likely due to their high GWP (1030, 675 and 2310, respectively). Moreover, the composition analysis reveals that mixtures including HCs show in general lower scores. Focusing on the high score side of the bar chart, it is visible that the best options are characterized by large amount of HFOs (R1234ze, R1234yf), which are also the fluids that guarantee lowest value of GWP, close to zero.
Two solutions have been underlined in Figure 2: i) the optimum mixture (M40), with the highest score of 70.4, is a ternary mixture of R134a (42.3%), R1234yf (16.2%) and R1234ze (41.5%); ii) the mixture named M0, namely the best R134a-free option, is a binary mixture of R1234yf (13%) and R1234ze

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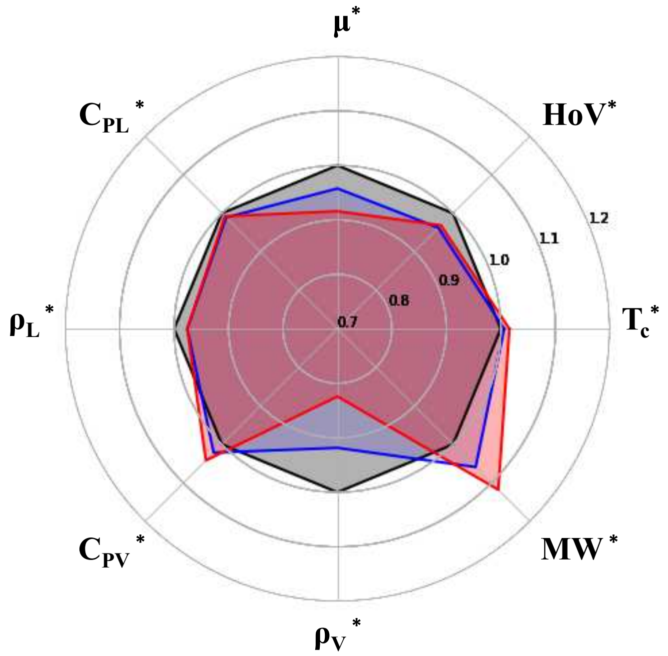
(87%) with a 69.9 value of the objective function. The radar chart in Figure 3 shows the comparison between R134a and the two mixtures M40 and M0. The properties reporting the symbol * are normalized against those of R134a.



Property	R134a	M40	M0
μ (mPa·s)	0.1052	0.1008	0.0964
HoV (kJ/kg)	123.2	119.3	118.5
T_C (K)	374.2	380.6	376.5
MW (g/mol)	102	108	114
ρ_V (kg/m^3)	118.0	97.3	108.4
C_{PV} (kJ/kg/K)	0.79	0.82	0.81
ρ_L (kg/m^3)	991.6	967.7	967.7
C_{PL} (kJ/kg/K)	1.28	1.27	1.26

Figure 3: Radar chart of the optimization targets normalized against R134a (φ/φ_{R134a}) for the highest score mixture M40 (blue), and the best R134a-free mixture M0 (red) in comparison with R134a (black). Punctual values are also provided in the table.

In Figure 3 it is visible that the optimum mixture (M40) can match the properties of R134a with a degree of accuracy between the 98% and the 95%, except for the vapour phase density, which is underestimated of around the 10%. The GWP of the M40 mixture is 608, and the Jacob number is 0.37. The mixture M0 behaves as the M40 mixture in terms of heat of vaporization, critical temperature, heat capacity, liquid density, viscosity, whilst a slight reduction of the match can be seen for molecular weight (10% increase) and vapour density (20% decrease). The values of GWP and Jacob number for the M0 mixture are 5.7 and 0.37, respectively.

Regarding the discrepancy of the values of some properties between optimal mixtures and target, some issues should be considered, especially in case of retrofitting of an existing ORC system originally operated with R134a. For example, the lower HoV value of both optimal solutions compared to R134a, together with the lower values of vapour density, suggest that the resulting volume flow rate would be slightly higher in both pump and expander, in order to recover the same thermal input from the heat source. However, in this example, the modest differences compared to R134a should not modify significantly the system performance in case of retrofit, and also the required modifications to the existing equipment should be limited.

In conclusion, the HFOs binary mixture M0 designed by the proposed tool can be an attractive alternative as a working fluid for the retrofit of ORC plants in place of R134a. Indeed, according to the match in Figure 3, the M0 can be operated without significant adjustments on piping, pump etc., while taking advantage of the GWP 99+% reduction and the lack of R134a. However, it must be considered that the Jacob number of both mixtures is larger than that of R134a (0.35), suggesting that a slight penalization of the thermodynamic efficiency is expected, if the mixture works in a cycle with the selected values of hot and cold temperature.

Main next developments will be dedicated, in addition to a general improvement of the mixing rules, to the introduction of the mixture flammability among the properties considered in the optimization, and the integration in the algorithm of a simplified model of the ORC system, with the aim of providing a stronger validation of the method capabilities.

Furthermore, the algorithm can be used to address the design of an overall 'best replacing mixture', by setting up the accomplishment of plant-related targets (e.g., net power output, best efficiency) as well as environmental and safety constraints (e.g., low GWP, low flammability). Under this framework, significant changes should be applied: i) definition of a new objective function based on general plant-related parameters instead of fluid properties; ii) reviewing the list of pure components; iii) include a model of an ORC test bench in order to test the formulated mixture as working fluid runtime, then, evaluate the next composition based on the performance of the virtual plant. It must be considered that at each iteration of the optimizer, the ORC model would perform a number of sub-iterations for solving the operating cycle. As a result, in order to limit the computation time (which would increase from tens of seconds up to hours), the user should put more care in determining the maximum epochs, the exploration-exploitation split, providing the code with guidelines about the pure fluids that must be used with larger amount.

4 CONCLUSIONS

This paper deals with the implementation and testing of an optimization algorithm able to design working fluid mixtures for ORC systems. The algorithm employs a probabilistic Bayesian methodology to create blends of organic fluids. The scope of the optimization routine is to maximize a multi-objective function, which includes a set of properties and performance indexes that are considered representative of the fluid behaviour during operations. After the tuning and validation of the mixing rules implemented in the algorithm, the tool was run with the purpose of designing a low-GWP surrogate mixture for R134a, considering an application characterized by vaporization temperature of 75 °C and condensation temperature of 30 °C. The tool has designed 193 mixtures, with a score varying between 55 and 70.4. The solution with the highest value of the optimization function is a ternary mixture of R134a (42%), R1234yf (16%) and R1234ze (42%), with GWP value around 600. The best solution without any trace of R134a is a binary mixture of two HFOs (R1234yf, R1234ze), with almost null GWP (5.7).

The strength of the proposed tool lies in its simplicity, low numerical effort and good performance in mixture design. Moreover, it is based on open-source software (Python and CoolProp) and can be applied to any mixture selection procedure for preliminary screening. Future developments will be aimed at improving the algorithm performance, in terms of accuracy of the mixing rules and definition of more convenient indexes to estimate the real performance of the fluid at the specified working conditions. 280

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This book contains the compilation of works contributed to the *7th International Seminar on Organic Rankine Cycle Power Systems* (ORC 2023), held in Seville between the 4th and 6th of September 2023. The event was hosted by Universidad de Sevilla on behalf of the Knowledge Centre on Organic Rankine Cycle Technology (KCORC), incorporated in The Netherlands.

The ORC conference, organized biennially, stems as the only conference that is specific to ORC technology, therefore gathering a diverse community whose affiliation spans across all the interested stakeholders, not only in this particular technology but also and in a broader context, in the energy transition. Original equipment manufacturers, professional associations, end-users, investors, policy makers, academics, scientists feel at home at ORC 2023.

The almost 100 proceedings in this book cover a wide variety of topics, from fundamentals to system integration through component design, accounting for thermodynamic performance as well as component design. In addition to this, and as a new track in 2023, works on heat pump technology were also accepted in order to raise awareness of the strong ties between both technologies, specifically in energy storage applications.

This book provides an excellent overview of the current maturity of power systems based on Organic Rankine Cycle technology for applications as diverse as geothermal and waste heat recovery in industry or downstream of other prime movers (e.g., marine applications). It is also an excellent source of information to understand the current challenges faced by the technology, stemming from a very competitive market and increasingly stringent environmental regulations.

The organizers of ORC 2023 hope that the reader finds this work as exciting as the attendees to the conference and, maybe, make the decision to join the 8th edition to the conference in 2025.

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